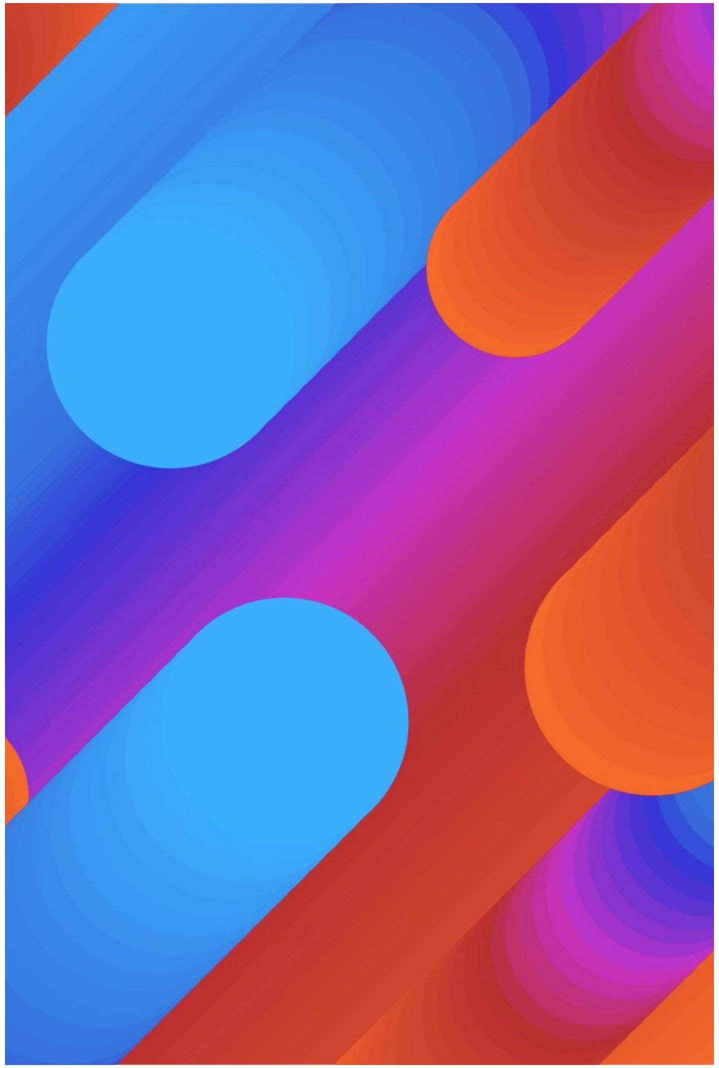


Exploration: Identify creative content in users’ curated digital life

ANGEL HSING-CHI HWANG

LAURA HERMAN

MIXED METHOD APPROACH TO UNDERSTAND THE MEANINGS OF CREATIVITY

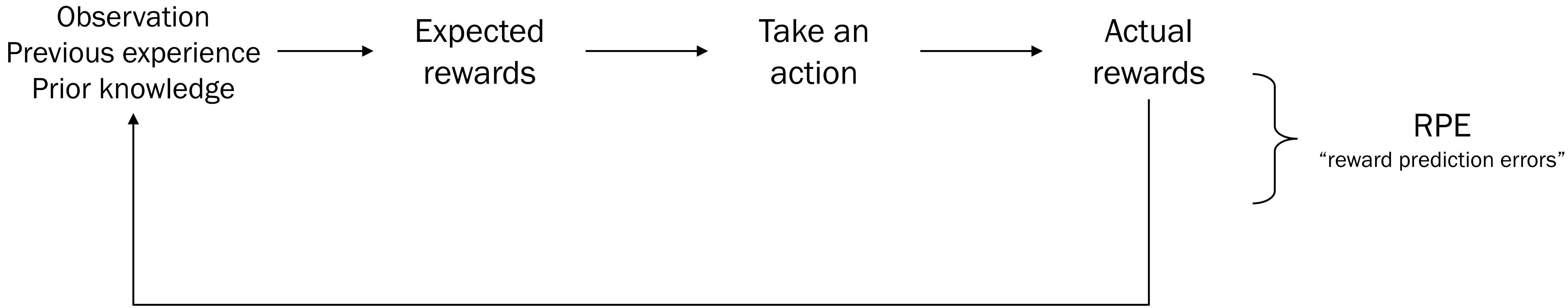
- Qualitative – Focus group
- Quantitative – Behance site visit data

SOME KEY TAKEAWAYS FROM A PREVIOUS STUDY

- Creativity as a process
- Evaluation of creative content is multi-dimensional
- Perception and concept of creativity update constantly

CONTENT SITE VISIT DATA ANALYSIS

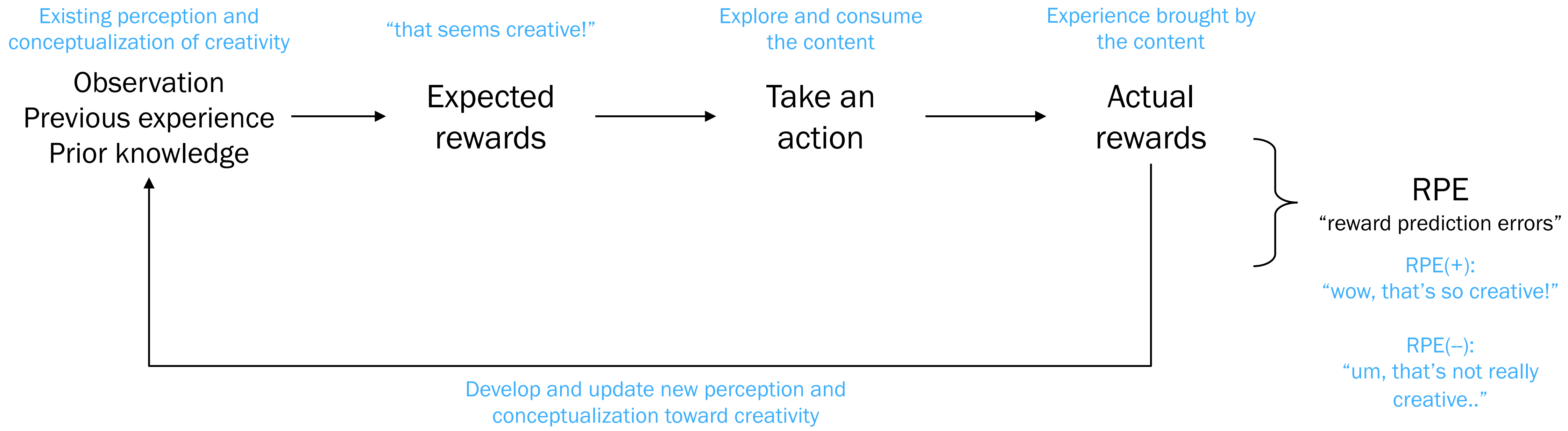
❖ **Reinforcement learning** as an approach to study exploration and novelty-seeking behavior



*David Silver's wonderful intro to reinforcement learning: https://www.youtube.com/watch?v=2pWv7GOvuf0&t=2031s

CONTENT SITE VISIT DATA ANALYSIS

❖ **Reinforcement learning** as an approach to study exploration and novelty-seeking behavior



Structured, uncertainty-driven exploration in real-world consumer choice

Eric Schulz[a,1,2], Rahul Bhui[a,1], Bradley C. Love[b,c], Bastien Brier[d], Michael T. Todd[d], and Samuel J. Gershman[a]

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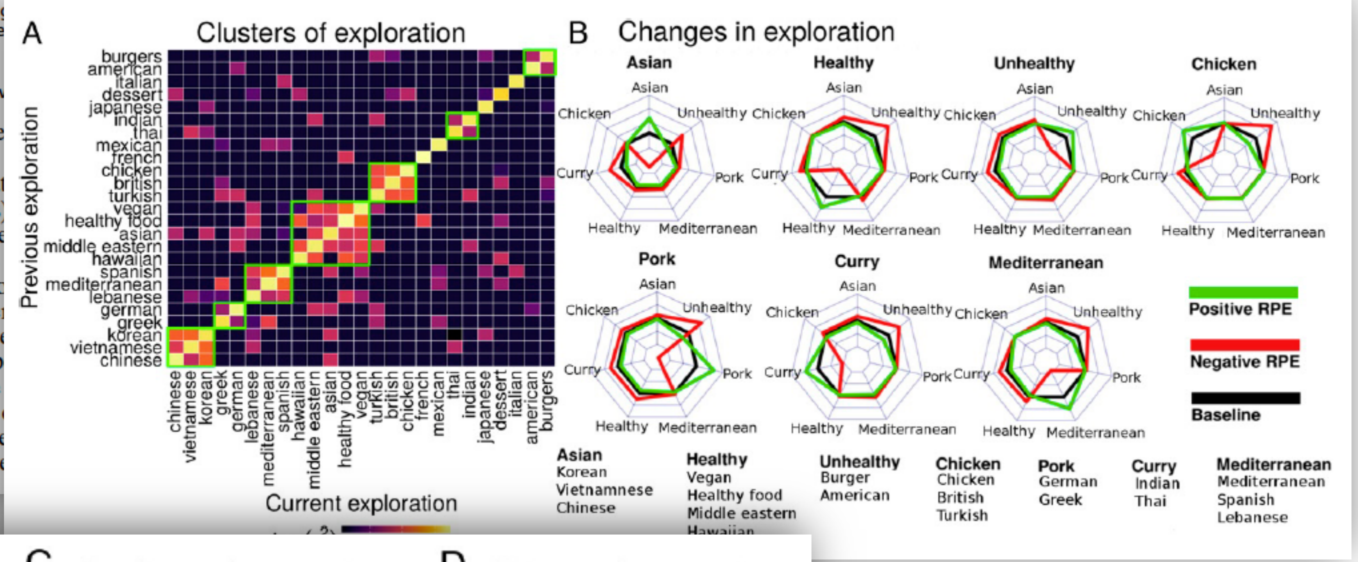
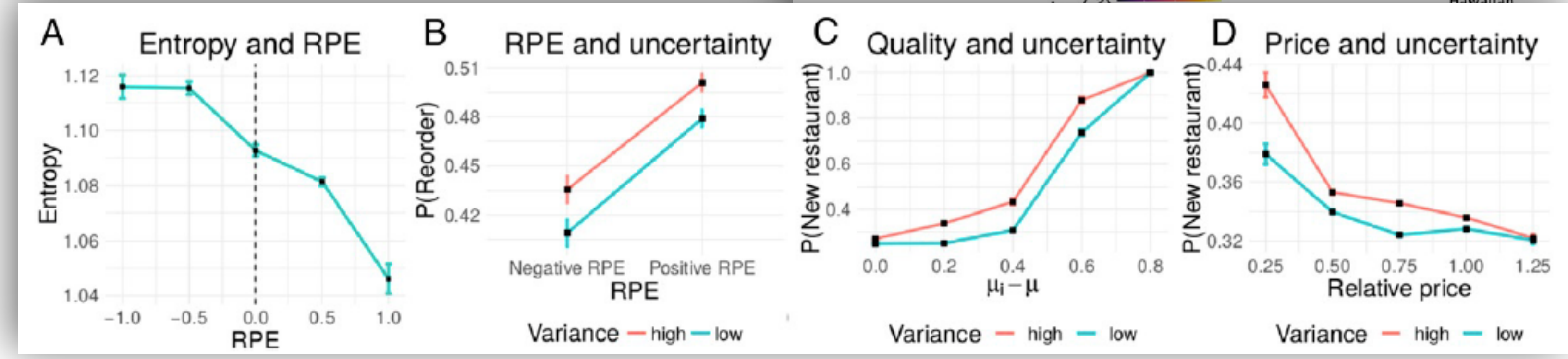
Edited by Richard M. Shiffrin, Indiana University, Bloomington, IN, and approved May 23, 2019 (received for rev

Making good decisions requires people to appropriately explore their available options and generalize what they have learned. While computational models can explain exploratory behavior in constrained laboratory tasks, it is unclear to what extent these models generalize to real-world choice problems. We investigate the factors guiding exploratory behavior in a dataset consisting of 195,333 customers placing 1,613,967 orders from a large online food delivery service. We find important hallmarks of adaptive exploration and generalization, which we analyze using computational models. In particular, customers seem to engage in uncertainty-directed exploration and use feature-based generalization to guide their exploration. Our results provide evidence that people use sophisticated strategies to explore complex, real-world environments.

it is unclear whether the
real-world choices.

Our results suggest that
unexperienced restaurants
rant quality and make be
is indeed risky and leads
people are more likely to
side is lower due to higher
we show that customers'
account not only the prosp
rant, but also the degree
mates. Consistent with an
ration policy, they prefer
and are more likely to r
uncertainties.





Schulz et al., 2019

Learning to explore options on food delivery apps

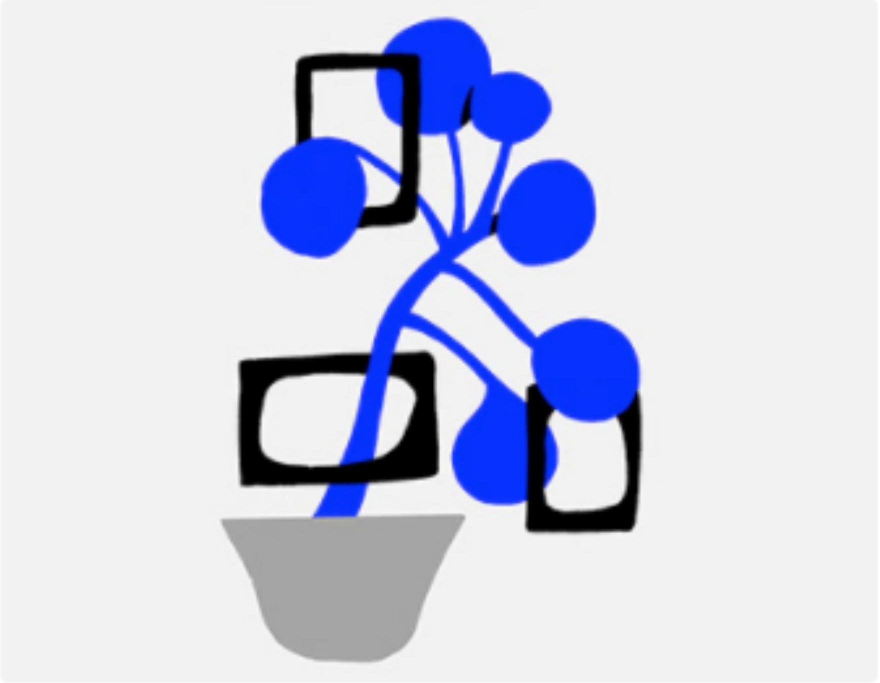
Shake Shack (4309 La Jolla Village Drive)

$0.49 Delivery Fee • 25–35 Min • $

4.8

American • Burgers

Learning to identify creative content online



Timo Kuilder

541 2.9k

*Behance also offers filtered search by medium type

*can also do some visual analysis with the displayed images

CONTENT SITE VISIT DATA ANALYSIS

❖ **Reinforcement learning** as an approach to study exploration and novelty-seeking behavior

Artist, likes, views, medium type

Observation
Previous experience
Prior knowledge

→

“that seems creative!”

Expected rewards

→

Explore and consume the content

Take an action

→

Experience brought by the content

Actual rewards

RPE
“reward prediction errors”

Displayed vs. actual like per view

Develop and update new perception and conceptualization toward creativity

Trackable behaviors:

- Like/share the content
- Follow the artist
- Explore other works of the same artists
- Explore works of relevant artists

CONTENT SITE VISIT DATA ANALYSIS

IVs

Clues on displayed snapshots:

- Artists
- Medium type
- Images
- Likes
- Views

Moderators

Individual difference:

- Demographics
- Data obtained from user profiles?

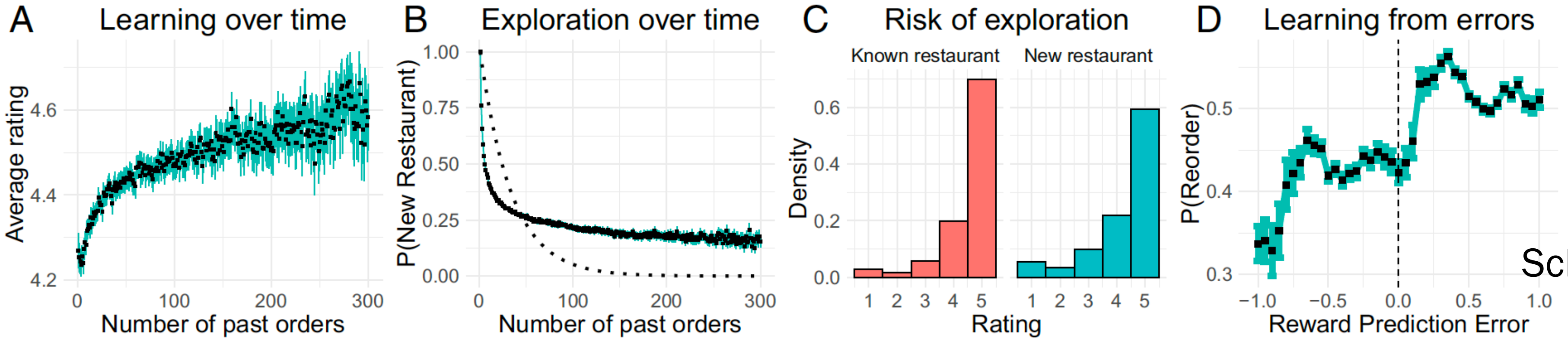
DVs

Trackable behaviors:

- Like/share the content
- Follow the artist
- Explore other works of the same artists
- Explore works of relevant artists

LEARNING & EXPLORATION OVER TIME

RL Theoretical Construct	Operationalize to a Food Delivery app (Schulz et al., 2019)	Operationalize to a content website
Agent learns from past experiences	generalization from overall food delivery experience: Positive correlation between # of past orders and ratings	Correlation between # of past visit and ratings
With reduced uncertainty, an agent reduces random exploration overtime	Customers sampled fewer new restaurants over time (negative correlation between # of past orders and the probability of sampling a new restaurant)	correlation between # of past visit and probability of sampling a new artist's profile
Exploration comes at a cost	Explored restaurants showed a lower average rating *exploration = whether a given order was the first time a customer had ordered from that particular restaurant	exploration = when a visit to a piece of content was the first time a customer viewed from that particular artist
Agent learns from past actions	generalization by ordering from a particular restaurant: probability of reordering from a restaurant as a function of their reward prediction RPE = the difference between expected quality of a restaurant (i.e., the restaurant's average rating at the time of the order) and the actual pleasure customers perceived after they consumed the order (i.e., indicates by their own rating of the order)	RPE= the difference between a piece of content's (std.) likes/views at the time being clicked by a user, and the probability of whether the user actually take any action after viewing the content.
Agent will update her sampling behavior after receiving either a positive or negative RPE	Correlation between RPE and the probability of reordering (customers were more likely to reorder from a restaurant after an experience that was better than expected, i.e., positive RPE)	correlation between RPE and the probability of revisiting a piece of content or revisiting an artist's profile.



Schulz et al., 2019